SENTIMENT ANALYSIS

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A Twitter sentiment analysis determines negative, positive, or neutral emotions within the text of a tweet using NLP and ML models. Sentiment analysis or opinion mining refers to identifying as well as classifying the sentiments that are expressed in the text source. Tweets are often useful in generating a vast amount of sentiment data upon analysis. These data are useful in understanding the opinion of people on social media for a variety of topics.

What is Twitter Sentiment Analysis?

Twitter sentiment analysis analyzes the sentiment or emotion of tweets. It uses natural language processing and machine learning algorithms to classify tweets automatically as positive, negative, or neutral based on their content. It can be done for individual tweets or a larger dataset related to a particular topic or event.

Why is Twitter Sentiment Analysis Important?

1. Understanding Customer Feedback: By analyzing the sentiment of customer feedback, companies can identify areas where they need to improve their products or services.
2. Reputation Management: Sentiment analysis can help companies monitor their brand reputation online and quickly respond to negative comments or reviews.
3. Political Analysis: Sentiment analysis can help political campaigns understand public opinion and tailor their messaging accordingly.
4. Crisis Management: In the event of a crisis, sentiment analysis can help organizations monitor social media and news outlets for negative sentiment and respond appropriately.
5. Marketing Research: Sentiment analysis can help marketers understand consumer behavior and preferences, and develop targeted advertising campaigns.

How to Do Twitter Sentiment Analysis Dataset?

In this article, we aim to analyze Twitter sentiment analysis Dataset using machine learning algorithms, the sentiment of tweets provided from the **Sentiment140 dataset** by developing a machine learning pipeline involving the use of three classifiers (**Logistic Regression, Bernoulli Naive Bayes, and SVM**)along with using **Term Frequency- Inverse Document Frequency** (**TF-IDF)**. The performance of these classifiers is then evaluated using **accuracy** and **F1 Scores**.

For data preprocessing, we will be using Natural Language Processing's (NLP) NLTK library.

Twitter Sentiment Analysis: Problem Statement

In this project, we try to implement an NLP **Twitter sentiment analysis model** that helps to overcome the challenges of sentiment classification of tweets. We will be classifying the tweets into positive or negative sentiments. The necessary details regarding the dataset involving the Twitter sentiment analysis project are:

The dataset provided is the **Sentiment140 Dataset** which consists of **1,600,000 tweets** that have been extracted using the Twitter API. The various columns present in this Twitter data are:

- **target:** the polarity of the tweet (positive or negative)
- **ids:** Unique id of the tweet
- **date:** the date of the tweet
- **flag:** It refers to the query. If no such query exists, then it is NO QUERY.
- **user:** It refers to the name of the user that tweeted
- **text:** It refers to the text of the tweet

Twitter Sentiment Analysis Dataset: Project Pipeline

The various steps involved in the **Machine Learning Pipeline** are:

- Import Necessary Dependencies
- Read and Load the Dataset
- Exploratory Data Analysis
- Data Visualization of Target Variables
- Data Preprocessing
- Splitting our data into Train and Test sets.
- Transforming Dataset using TF-IDF Vectorizer
- Function for Model Evaluation
- Model Building
- Model Evaluation

Step-1: Import the Necessary Dependencies

```
# utilities import re
import numpy as np
import pandas as pd
# plotting import seaborn as sns
from wordcloud import WordCloud
import matplotlib.pyplot as plt
# nltk
from nltk.stem import WordNetLemmatizer
# sklearn
from sklearn.svm import LinearSVC from sklearn.naive_bayes import
BernoulliNB from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import train_test_split from
sklearn.feature_extraction.text import TfidfVectorizer from
sklearn.metrics import confusion_matrix, classification_report
```

Step-2: Read and Load the Dataset

```
Importing the dataset
DATASET_COLUMNS=['target','ids','date','flag','user','text']
DATASET_ENCODING = "ISO-8859-1"
df = pd.read_csv('Project_Data.csv', encoding=DATASET_ENCODING,
names=DATASET_COLUMNS)
df.sample(5)
```

Step-3: Exploratory Data Analysis

1.Five top records of data **df.head()**

2.Columns/features in data **df.columns**

3: Length of the dataset

```
print('length of data is' , len(df))
```

4: Shape of data

```
df. Shape
```

5: Data information

```
df.info()
```

6.Datatypes of all column

```
df.dtypes
```

7: Checking for null value

```
np.sum(df.isnull().any(axis=1))
```

8: Rows and columns in the dataset

```
print('Count of columns in the data is:  ', len(df.columns))
 print('Count of rows in the data is:  ', len(df))
```

Step-4: Data Visualization of Target Variables

Plotting the distribution for dataset. ax = df.groupby('target').count().plot(kind='bar', title='Distribution of data',legend=False) ax.set_xticklabels(['Negative','Positive'], rotation=0) # Storing data in lists. text, sentiment = list(df['text']), list(df['target'])

```
import seaborn as sns
sns.countplot(x='target', data=df)
```

Step-5: Data Preprocessing Step-5: Data Preprocessing

In the above-given problem statement, before training the model, we performed various pre-processing steps on the dataset that mainly dealt with removing stopwords, removing special characters like emojis, hashtags, etc. The text document is then converted into lowercase for better generalization.

Subsequently, the punctuations were cleaned and removed, thereby reducing the unnecessary noise from the dataset. After that, we also removed the repeating characters from the words along with removing the URLs as they do not have any significant importance.

At last, we then performed **Stemming(reducing the words to their derived stems)** and **Lemmatization(reducing the derived words to their root form, known as lemma)** for better results.

5.1: Selecting the text and Target column for our further analysis

```
data=df[['text','target']]
```

5.2: Replacing the values to ease understanding. (Assigning 1 to Positive sentiment 4)

```
data['target'] = data['target'].replace(4,1)
```

5.3: Printing unique values of target variables

```
data['target'].unique()
```

5.4: Separating positive and negative tweets

```
data_pos = data[data['target'] == 1]
data_neg = data[data['target'] == 0]
```

5.5: Taking one-fourth of the data so we can run it on our machine easily

```
data_pos = data_pos.iloc[:int(20000)]
data_neg = data_neg.iloc[:int(20000)]
```

5.6: Combining positive and negative tweets

```
dataset = pd.concat([data_pos, data_neg])
```

5.7: Making statement text in lowercase

```
dataset['text']=dataset['text'].str.lower()
dataset['text'].tail()
```

Output:

```
19995    not much time off this weekend, work trip to m...
19996                             one more day of holidays
19997    feeling so down right now .. i hate you damn h...
19998    geez,i hv to read the whole book of personalit...
19999    i threw my sign at donnie and he bent over to ...
Name: text, dtype: object
```

5.8: Defining set containing all stopwords in English.

```
stopwordlist = ['a', 'about', 'above', 'after', 'again', 'ain', 'all', 'am', 'an',
             'and','any','are', 'as', 'at', 'be', 'because', 'been', 'before',
             'being', 'below', 'between','both', 'by', 'can', 'd', 'did', 'do',
             'does', 'doing', 'down', 'during', 'each','few', 'for', 'from',
             'further', 'had', 'has', 'have', 'having', 'he', 'her', 'here',
             'hers', 'herself', 'him', 'himself', 'his', 'how', 'i', 'if', 'in',
             'into','is', 'it', 'its', 'itself', 'just', 'll', 'm', 'ma',
             'me', 'more', 'most','my', 'myself', 'now', 'o', 'of', 'on', 'once',
             'only', 'or', 'other', 'our', 'ours','ourselves', 'out', 'own', 're','s', 'same', 'she', "shes", 'should', "shouldve",'so',
'some', 'such',
             't', 'than', 'that', "thatll", 'the', 'their', 'theirs', 'them',
             'themselves', 'then', 'there', 'these', 'they', 'this', 'those',
             'through', 'to', 'too','under', 'until', 'up', 've', 'very', 'was',
             'we', 'were', 'what', 'when', 'where','which','while', 'who', 'whom',
             'why', 'will', 'with', 'won', 'y', 'you', "youd","youll", "youre",
             "youve", 'your', 'yours', 'yourself', 'yourselves']
```

5.9: Cleaning and removing the above stop words list from the tweet text

```
STOPWORDS = set(stopwordlist) def cleaning_stopwords(text):     return "
".join([word for word in str(text).split() if word not in STOPWORDS])
dataset['text'] = dataset['text'].apply(lambda text: cleaning_stopwords(text))
dataset['text'].head()
```

Output:

```
800000                  love @health4uandpets u guys r best!!
800001    im meeting one besties tonight! cant wait!! - ...
800002    @darealsunisakim thanks twitter add, sunisa! g...
800003    sick really cheap hurts much eat real food plu...
800004                        @lovesbrooklyn2 effect everyone
Name: text, dtype: object
```

5.10: Cleaning and removing punctuations

```
import string english_punctuations =
string.punctuation punctuations_list =
english_punctuations def
cleaning_punctuations(text):
  translator = str.maketrans('', '', punctuations_list)
return text.translate(translator)
dataset['text']= dataset['text'].apply(lambda x: cleaning_punctuations(x))
dataset['text'].tail()
```

Output:

```
19995    not much time off weekend work trip malmï¿½ fr...
19996                                      one day holidays
19997                           feeling right  hate damn humprey
19998    geezi hv read whole book personality types emb...
19999    threw sign donnie bent over get but thingee ma...
Name: text, dtype: object
```

5.11: Cleaning and removing repeating characters

```
def cleaning_repeating_char(text):
return re.sub(r'(.)1+', r'1', text)
dataset['text'] = dataset['text'].apply(lambda x: cleaning_repeating_char(x))
dataset['text'].tail()
```

Output:

```
19995    not much time of wekend work trip malmï¿½ fris...
19996                                      one day holidays
19997                            feling right hate damn humprey
19998    gezi hv read whole bok personality types embar...
19999    threw sign donie bent over get but thinge made...
Name: text, dtype: object
```

5.12: Cleaning and removing URLs

```
def cleaning_URLs(data):
   return re.sub('((www.[^s]+)|(https?://[^s]+))',' ',data) dataset['text']
= dataset['text'].apply(lambda x: cleaning_URLs(x))
dataset['text'].tail()
```

Output:

```
19995    not much time of wekend work trip malmï¿½ fris...
19996                                      one day holidays
19997                            feling right hate damn humprey
19998    gezi hv read whole bok personality types embar...
19999    threw sign donie bent over get but thinge made...
Name: text, dtype: object
```

5.13: Cleaning and removing numeric numbers

```
def cleaning_numbers(data):
    return re.sub('[0-9]+', '', data)
dataset['text'] = dataset['text'].apply(lambda x: cleaning_numbers(x))
dataset['text'].tail()
```

Output:

```
19995     not much time of wekend work trip malmï¿½ fris...
19996                                      one day holidays
19997                          feling right hate damn humprey
19998     gezi hv read whole bok personality types embar...
19999     threw sign donie bent over get but thinge made...
Name: text, dtype: object
```

5.14: Getting tokenization of tweet text

```
from nltk.tokenize import RegexpTokenizer tokenizer
= RegexpTokenizer(r'w+')
dataset['text'] = dataset['text'].apply(tokenizer.tokenize) dataset['text'].head()
```

Output:

```
800000              [love, healthuandpets, u, guys, r, best]
800001     [im, meting, one, besties, tonight, cant, wait...
800002     [darealsunisakim, thanks, twiter, ad, sunisa, ...
800003     [sick, realy, cheap, hurts, much, eat, real, f...
800004                     [lovesbroklyn, efect, everyone]
Name: text, dtype: object
```

5.15: Applying stemming

```
import nltk st =
nltk.PorterStemmer() def
stemming_on_text(data):
    text = [st.stem(word) for word in data]
return data
dataset['text']= dataset['text'].apply(lambda x: stemming_on_text(x))
dataset['text'].head()
```

Output:

```
800000                [love, healthuandpets, u, guys, r, best]
800001     [im, meting, one, besties, tonight, cant, wait...
800002     [darealsunisakim, thanks, twiter, ad, sunisa, ...
800003     [sick, realy, cheap, hurts, much, eat, real, f...
800004                     [lovesbroklyn, efect, everyone]
Name: text, dtype: object
```

5.16: Applying lemmatizer

```
lm = nltk.WordNetLemmatizer() def
lemmatizer_on_text(data):
    text = [lm.lemmatize(word) for word in data]
return data
dataset['text'] = dataset['text'].apply(lambda x: lemmatizer_on_text(x))
dataset['text'].head()
```

Output:

```
800000                [love, healthuandpets, u, guys, r, best]
800001     [im, meting, one, besties, tonight, cant, wait...
800002     [darealsunisakim, thanks, twiter, ad, sunisa, ...
800003     [sick, realy, cheap, hurts, much, eat, real, f...
800004                     [lovesbroklyn, efect, everyone]
Name: text, dtype: object
```

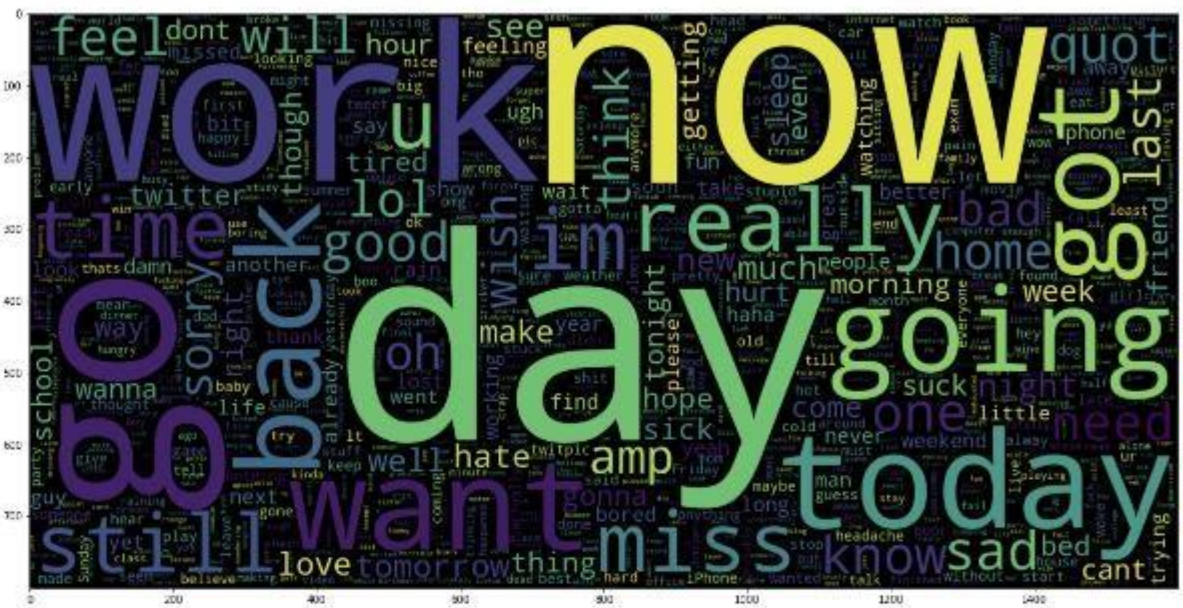
5.17: Separating input feature and label

```
X=data.text y=data.target
```

5.18: Plot a cloud of words for negative tweets

```
data_neg = data['text'][:800000] plt.figure(figsize
= (20,20))
wc = WordCloud(max_words = 1000 , width = 1600 , height = 800,
        collocations=False).generate(" ".join(data_neg))
plt.imshow(wc)
```

Output:



5.19: Plot a cloud of words for positive tweets

```
data_pos = data['text'][800000:]
wc = WordCloud(max_words = 1000 , width = 1600 , height = 800,
            collocations=False).generate(" ".join(data_pos))

plt.figure(figsize = (20,20)) plt.imshow(wc)
```

Output:

Step-6: Splitting Our Data Into Train and Test Subsets

```
# Separating the 95% data for training data and 5% for testing data
X_train, X_test, y_train, y_test = train_test_split(X,y,test_size = 0.05, random_state =26105111)
```

Step-7: Transforming the Dataset Using TF-IDF Vectorizer

7.1: Fit the TF-IDF Vectorizer

```
vectoriser = TfidfVectorizer(ngram_range=(1,2), max_features=500000)
vectoriser.fit(X_train)
print('No. of feature_words: ', len(vectoriser.get_feature_names()))
```

Output:

```
No. of feature_words:  500000
```

7.2: Transform the data using TF-IDF Vectorizer

```
X_train = vectoriser.transform(X_train) X_test
= vectoriser.transform(X_test)
```

Step-8: Function for Model Evaluation

After training the model, we then apply the evaluation measures to check how the model is performing. Accordingly, we use the following evaluation parameters to check the performance of the models respectively:

- Accuracy Score
- Confusion Matrix with Plot
- ROC-AUC Curve

```
def model_Evaluate(model): #
Predict values for Test dataset
y_pred = model.predict(X_test)
# Print the evaluation metrics for the dataset.
print(classification_report(y_test, y_pred)) #
Compute and plot the Confusion matrix
cf_matrix = confusion_matrix(y_test, y_pred)
categories = ['Negative','Positive']
group_names = ['True Neg','False Pos', 'False Neg','True Pos']
group_percentages = ['{0:.2%}'.format(value) for value in cf_matrix.flatten() / np.sum(cf_matrix)]
labels = [f'{v1}n{v2}' for v1, v2 in zip(group_names,group_percentages)] labels =
np.asarray(labels).reshape(2,2)
sns.heatmap(cf_matrix, annot = labels, cmap = 'Blues',fmt = '', xticklabels
= categories, yticklabels = categories)
plt.xlabel("Predicted values", fontdict = {'size':14}, labelpad = 10)
plt.ylabel("Actual values" , fontdict = {'size':14}, labelpad = 10) plt.title
("Confusion Matrix", fontdict = {'size':18}, pad = 20)
```

Step-9: Model Building

In the problem statement, we have used three different models respectively :

- Bernoulli Naive Bayes Classifier
- SVM (Support Vector Machine)
- Logistic Regression

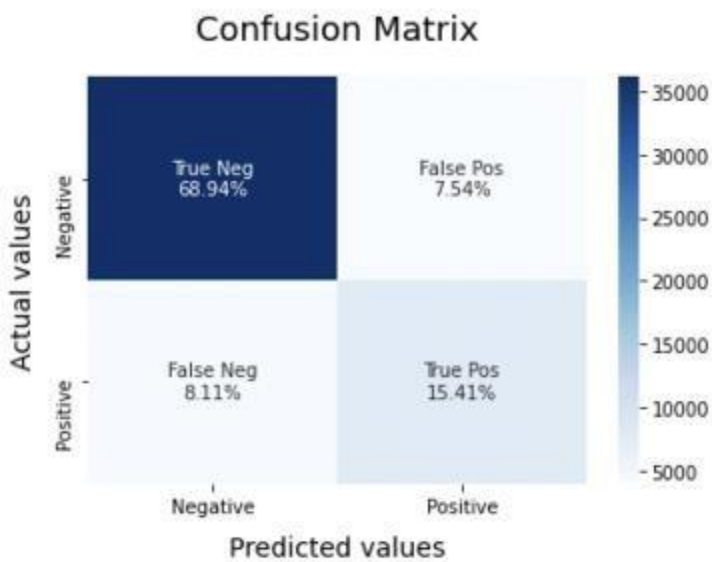
The idea behind choosing these models is that we want to try all the classifiers on the dataset ranging from simple ones to complex models, and then try to find out the one which gives the best performance among them.

8.1: Model-1

```
BNBmodel = BernoulliNB()
BNBmodel.fit(X_train, y_train)
model_Evaluate(BNBmodel)
y_pred1 = BNBmodel.predict(X_test)
```

Output:

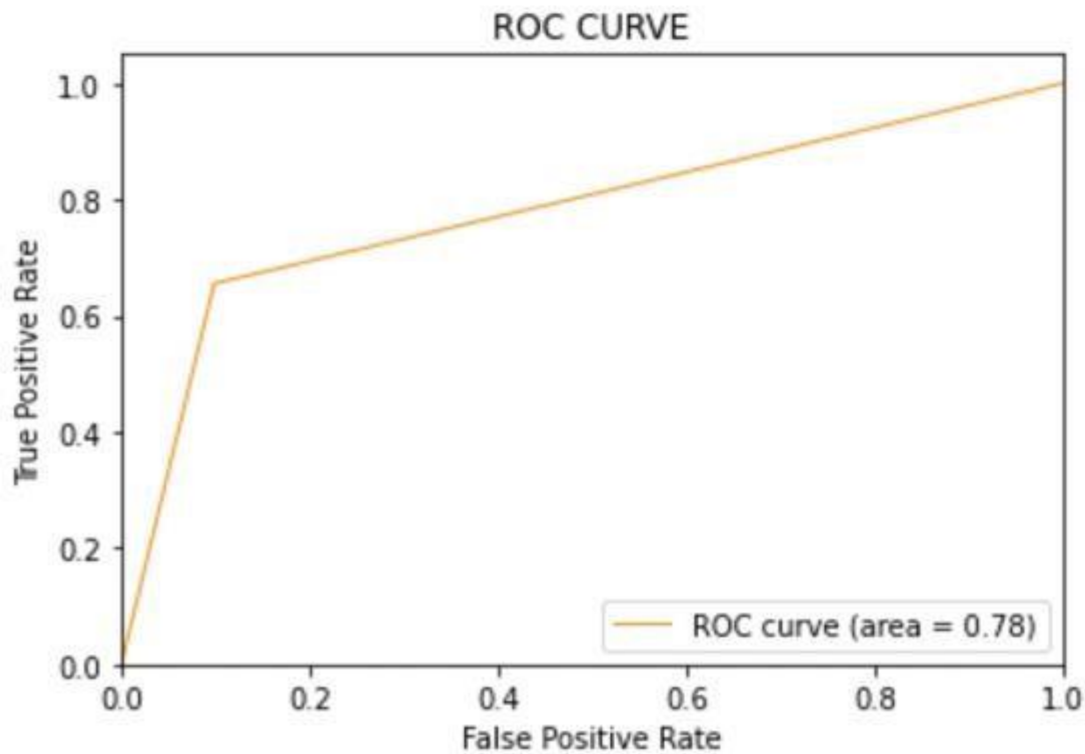
	precision	recall	f1-score	support
0	0.89	0.90	0.90	40097
1	0.67	0.66	0.66	12332
accuracy			0.84	52429
macro avg	0.78	0.78	0.78	52429
weighted avg	0.84	0.84	0.84	52429



8.2: Plot the ROC-AUC Curve for model-1

```
from sklearn.metrics import roc_curve, auc fpr,
tpr, thresholds = roc_curve(y_test, y_pred1)
roc_auc = auc(fpr, tpr) plt.figure()
plt.plot(fpr, tpr, color='darkorange', lw=1, label='ROC curve (area = %0.2f)' % roc_auc)
plt.xlim([0.0, 1.0]) plt.ylim([0.0, 1.05]) plt.xlabel('False Positive Rate') plt.ylabel('True
Positive Rate') plt.title('ROC CURVE') plt.legend(loc="lower right") plt.show()
```

Output:

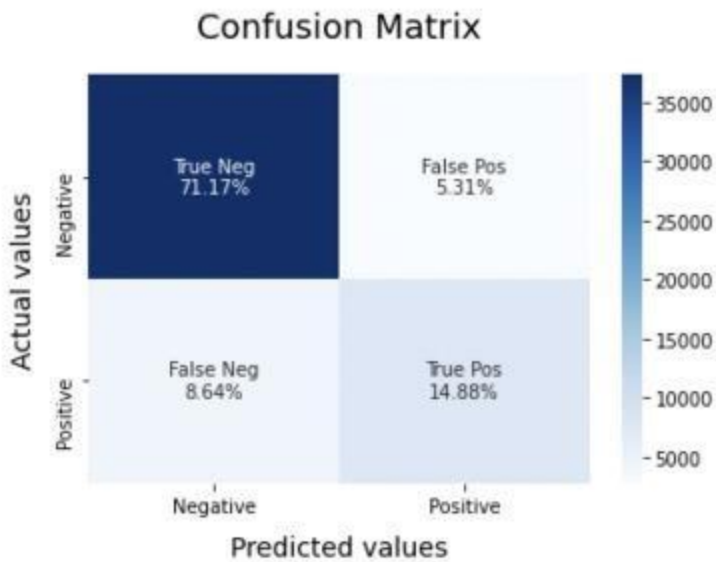


8.3: Model-2:

```
SVCmodel = LinearSVC()
SVCmodel.fit(X_train, y_train)
model_Evaluate(SVCmodel) y_pred2
= SVCmodel.predict(X_test)
```

Output:

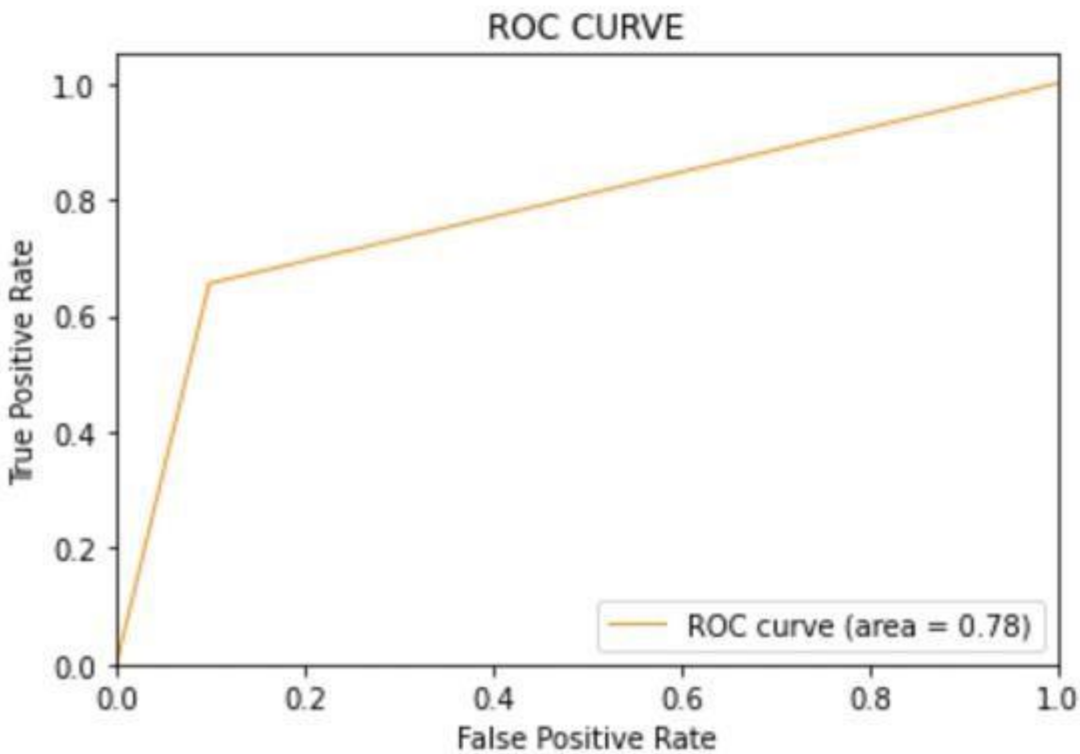
	precision	recall	f1-score	support
0	0.89	0.93	0.91	40097
1	0.74	0.63	0.68	12332
accuracy			0.86	52429
macro avg	0.81	0.78	0.80	52429
weighted avg	0.86	0.86	0.86	52429



8.4: Plot the ROC-AUC Curve for model-2

```
from sklearn.metrics import roc_curve, auc fpr,
tpr, thresholds = roc_curve(y_test, y_pred2)
roc_auc = auc(fpr, tpr) plt.figure()
plt.plot(fpr, tpr, color='darkorange', lw=1, label='ROC curve (area = %0.2f)' % roc_auc)
plt.xlim([0.0, 1.0]) plt.ylim([0.0, 1.05]) plt.xlabel('False Positive Rate') plt.ylabel('True
Positive Rate') plt.title('ROC CURVE') plt.legend(loc="lower right") plt.show()
```

Output:

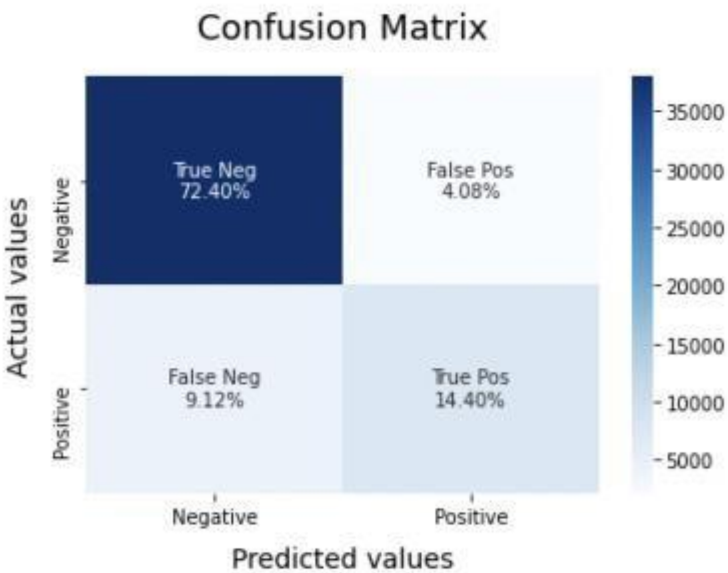


8.5: Model-3

```
LRmodel = LogisticRegression(C = 2, max_iter = 1000, n_jobs=-1)
LRmodel.fit(X_train, y_train)
model_Evaluate(LRmodel)
y_pred3 = LRmodel.predict(X_test)
```

Output:

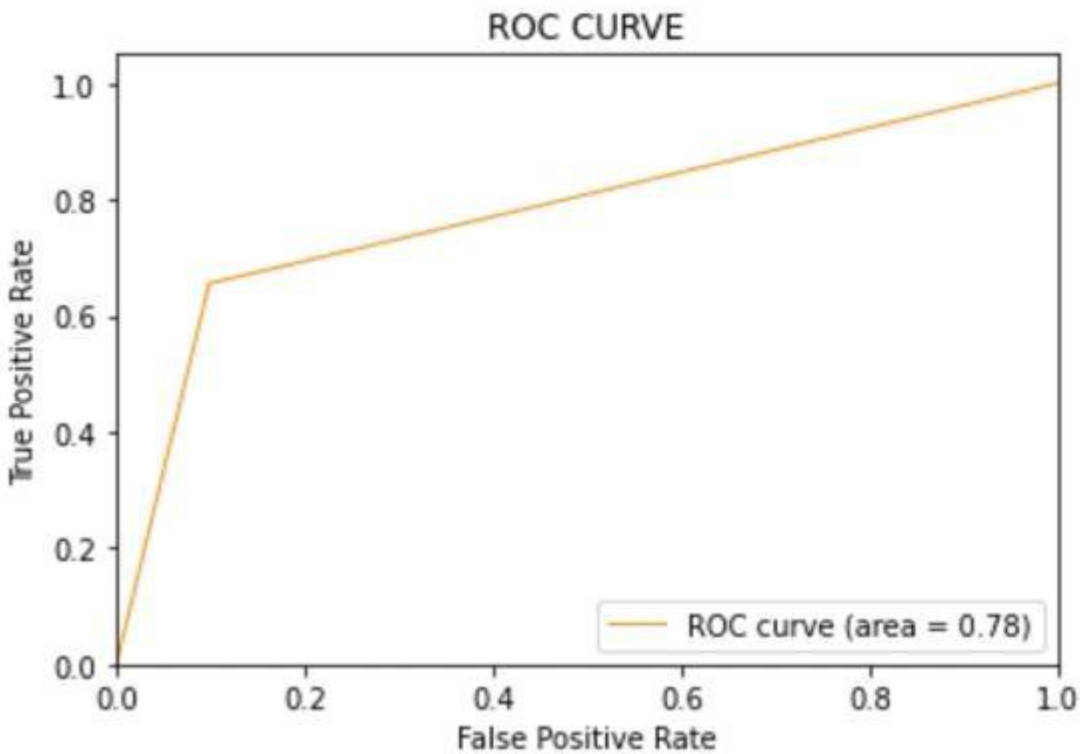
```
               precision    recall  f1-score   support

           0       0.89      0.95      0.92     40097
           1       0.78      0.61      0.69     12332

    accuracy                           0.87     52429
   macro avg       0.83      0.78      0.80     52429
weighted avg       0.86      0.87      0.86     52429
```



8.6: Plot the ROC-AUC Curve for model-3

```
from sklearn.metrics import roc_curve, auc fpr,
tpr, thresholds = roc_curve(y_test, y_pred3)
roc_auc = auc(fpr, tpr) plt.figure()
plt.plot(fpr, tpr, color='darkorange', lw=1, label='ROC curve (area = %0.2f)' % roc_auc)
plt.xlim([0.0, 1.0]) plt.ylim([0.0, 1.05]) plt.xlabel('False Positive Rate') plt.ylabel('True
Positive Rate') plt.title('ROC CURVE') plt.legend(loc="lower right") plt.show()
```

Output:



Step-10: Model Evaluation

Upon evaluating all the models, we can conclude the following details i.e.

Accuracy: As far as the accuracy of the model is concerned, Logistic Regression performs better than SVM, which in turn performs better than Bernoulli Naive Bayes.

F1-score: The F1 Scores for class 0 and class 1 are :

(a) For class 0: Bernoulli Naive Bayes(accuracy = 0.90) < SVM (accuracy =0.91) < Logistic Regression (accuracy = 0.92)

(b) For class 1: Bernoulli Naive Bayes (accuracy = 0.66) < SVM (accuracy = 0.68) < Logistic Regression (accuracy = 0.69)

AUC Score: All three models have the same ROC-AUC score.

We, therefore, conclude that the Logistic Regression is the best model for the above-given dataset.

In our problem statement, **Logistic Regression** follows the principle of **Occam's Razor,** which defines that for a particular problem statement, if the data has no assumption, then the simplest model works the best. Since our dataset does not have any assumptions and Logistic Regression is a simple model. Therefore, the concept holds true for the above-mentioned dataset.

Conclusion

We hope through this article, you got a basic of how twiiter Sentimental Analysis is used to understand public emotions behind people's tweets. As you've read in this article, Twitter Sentimental Analysis dataset helps us preprocess the data (tweets) using different methods and feed it into ML models to give the best accuracy.

Key Takeaways

- Twitter Sentimental Analysis is used to identify as well as classify the sentiments that are expressed in the text source.
- Logistic Regression, SVM, and Naive Bayes are some of the ML algorithms that can be used for Twitter Sentimental Analysis Python.